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Analyzing and Validating Employability Factors and Predictive Models for Computer Science Graduates: A Scientometric and Systematic Review

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Abstract: Promoting student employability stands as a central objective for educational institutions, often serving as a barometer of their effectiveness. However, the landscape of the job market is undergoing rapid transformation, driven by forces such as globalization, automation, and the rise of artificial intelligence (AI). In this study, we use scientometric analysis and a systematic literature review (SLR) to delve into recent trends and future trajectories within the realm of identifying, validating, and constructing predictive models for employability factors about computer science (CS) graduates. Our research encompasses 592 pertinent studies published between 2010 and 2023, sourced from Scopus, a pivotal academic database. Our SLR offers invaluable insights into the prevailing validation and predictive models for employability among CS graduates. Guided by our SLR, we propose that forthcoming research should explore the potential of innovative AI techniques to pinpoint key factors and elevate the precision of predictive models geared toward computer science graduates' employability.

Keywords: *CS graduate, prime factors, factor identification, factor validation, employability prediction, scientometric analysis, SLR*

1. Introduction

Ensuring that graduates find employment is a priority, for institutions as unemployment can hurt the economy [1]. Educational institutions annually increase the number of students graduating [2]. However, a major challenge arises from the mismatch between education productivity and labor market demands. This flawed system poses threats such as growth setbacks, high unemployment rates, and migration of graduates seeking job opportunities elsewhere [3]. Fixing these gaps comes at a cost [4]. To address this problem effectively higher education institutions must proactively take measures to enhance employability [5]. This not benefits individuals as well as contributes to the success of organizations they are part of and ultimately bolsters the entire country's economy [6]. Moreover, a considerable number of university-arranged internships and placements are highly competitive. As a result, interested candidates may not take advantage of these opportunities, and some individuals may not fully understand their potential benefits [7]. Computer science (CS) graduates face a slow transition in the workplace, according to research in India [8]. The research clearly shows that 15.98% of CS graduates are unemployed one year after graduation, which is higher than the overall average of 6.1%. Looking back, data up to 40 months after graduation show that in 2021-2022 in the cohort, 7.96% of CS graduates are unemployed [9]. While this represents an improvement on last year's figures, it remains the highest unemployment rate of any sector surveyed. CS graduates need to concern a range of skills, knowledge and abilities in the process of securing their jobs and roles [10]. In recent years, several artificial intelligence (AI) techniques, including machine learning (ML), deep learning (DL), and reinforcement learning [11]-[13], have become influential employability prediction tools. However, these studies often cover specific dimensions of the employability prediction domain, from predicting student behavior, soft skills to identifying key factors, validating these factors, and developing predictive models [14]-[16]. To fill these gaps, this paper provides not only an up-to-date systematic review of the literature on the main factors affecting employability and employability prediction models but also a quantitative conceptualization of the existing research [17]. This study is fundamentally driven by the pursuit of answers to the following pivotal research questions (RQs):

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- RQ1: To what extent has research explored the use of AI techniques in employability predictive models?
- RQ2: How have developments in this field evolved over recent years?
- RQ3: What prevailing themes define factors that influence employability and predictive models for graduate employability?
- RQ4: Which multidisciplinary knowledge areas are involved in applying AI techniques to employability predictive models?
- RQ5: What are the current research hotspots and future directions for the application of AI techniques in employability predictive models?

2. Methodology

In this study, we conducted a quantitative study with bibliometric and scientometric analysis to identify and evaluate SLR on the use of AI techniques for employability prediction. The initial phase of our research included activity analysis and scientific/bibliographic mapping [18]. It is a visual view of the relationships between different fields, subjects, specialties, individual scientific works, and authors. Fig. 1 shows the methodology used in our SLR, including data cleaning, application of inclusion criteria, and relevance, to help organize and classify different subjects according to their importance and studies [19].

2.1 Bibliometric analysis

2.1.1 Data sources

As shown in Table 1, the data collection was limited to journal articles that are part of the Scopus, Web of science, and Lens core collection.

2.1.2 Data cleaning

Our search was conducted to ensure that a comprehensive set of employment forecasting papers was included. Table 2 provides an overview of the original data set obtained from specific search strings. According to the inclusion criteria, we selected only articles published between 2010 and 2023. Exclusion criteria were designed to exclude articles not related to the area of predicting student outcomes [20][21].

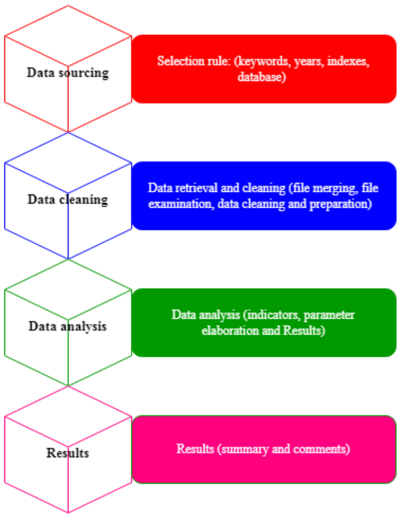

Fig. 1 Methodology used in this SLR

2.1.3 Data analysis

The corpus of articles for this analysis, which involved a thorough manual review process, included 289 relevant articles from Web of Science, 523 articles from SCOPUS, and 185 from LENS. To ensure the integrity of the data set, we carefully removed 419 duplicate articles and matched author names and journal titles, resulting in a set of 578 articles that were judiciously grouped into a single file. Detailed results and discussion arising from this SLR are described in Section 3.

Table 1 Database Description

Database	Search string	Results
Scopus	(("employability" or "CS employability") and ("prediction" or "predictive model") and ("AI" or "ML" or "DL")) Type: Article, language: English, publication year: 1970-2023	523
Web of science	(("employability" or "CS employability") and ("prediction" or "predictive model") and ("AI" or "ML" or "DL")) Type: Article, language: English, publication year: 1970-2023	289
Lens	(("employability" or "CS employability") and ("prediction" or "predictive model") and ("AI" or "ML" or "DL")) Type: Journal article, language: English, publication year: 1970-2023	185

2.4 Scientometric analysis

Scientometric analysis [22][23], an invaluable methodology, helps to measure research impact and discover citation relationships by using insights from academic databases to link specific academic fields. To provide multivariate analysis, this study used several analyses including keyword co-occurrence, author co-citation, journal co-citation, document co-citation, and clustering [24]. This progressive approach begins with keyword covariance and author covariance analysis, which provides a more complete picture of the research landscape. Citation analysis [25] then takes center stage in the paper, using clustering techniques and tagging of abstract terms to define different areas of research in the field of employability prediction. Fig. 2 shows the overall structure of bibliometric and scientometric analysis.

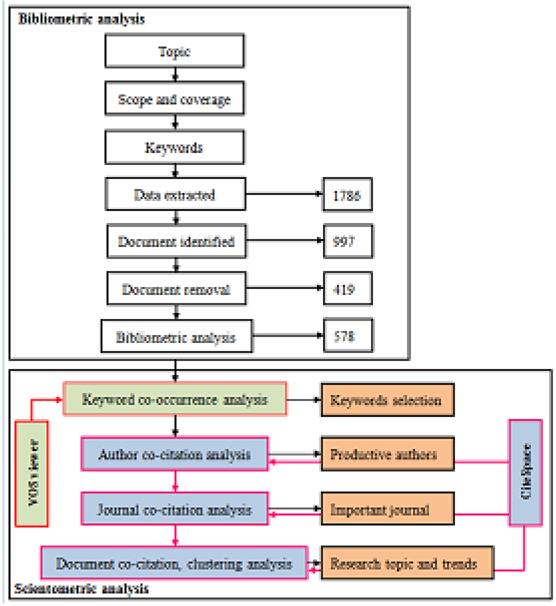

Fig. 2 Detailed methodology of this SLR with bibliometric and scientometric analysis

3. Results of bibliometric and scientometric analysis

Table 2 Key findings from SLR

Description	Value
Duration	1980-2023
Main sources	103
Number of Articles	578
Number of Journals	71
Citations per documents	1003
Citations per year	2489
Number of References	1245
Keywords	1047
Authors keywords	1568
Number of Authors	1875
Single-author documents	64
Multi-author documents	986
Authors per document	334
Co-authors per documents	87

3.1 Data Acquisition

Insights from the data analysis are summarized in the descriptive statistics presented in Table 2. Academic resources, including scientific articles, journal articles, and conference papers [26][27] dealing with the issue of construction planning, were systematically collected using a targeted keyword search of the Web of Science, Scopus, and LENS databases [28]. As shown in Fig. 3, the Scopus database, which provides extensive categorization and sorting capabilities.

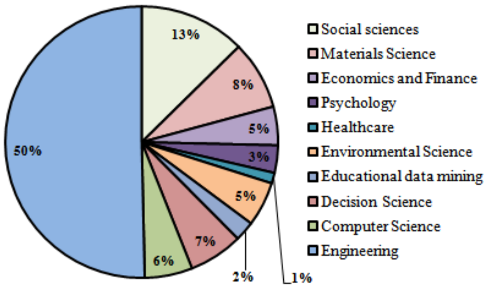

Fig. 3 Data acquisition from database

3.2 Keyword co-occurrence analysis

Keyword co-occurrence analysis [29][30] is powerful technique used in bibliometric and scientometric to understand dominant themes, emerging trends. When performing basic co-occurrence analysis using software tools such as VOSviewer [31], the process collects a dataset of documents related to research area, including titles, abstracts, and keywords.

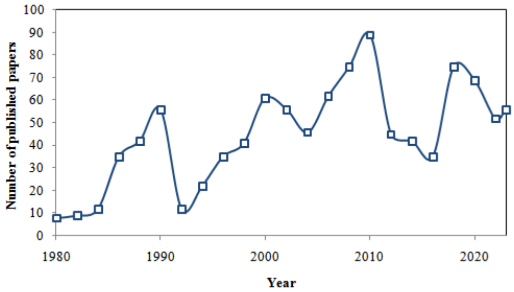

Fig. 4 Network from keyword co-occurrence analysis

Emerging trends that ensure further investigation were identified [32]. Fig. 4 shows the basic co-occurrence network with 42 nodes, 46 links and 39 total connection strengths. Table 3 summarizes the most common keywords, their occurrences, the average annual number of links published, and total link strength.

3.3 Author co-citation analysis

Author co-citation analysis [33][34] is bibliographic method that plays an important role in understanding author interactions and relationships in the context of educational research. To perform co-origin examination, analysts utilize specific programming devices, for example, CiteSpace [35]. In this, scientists gather a dataset of significant scholarly articles. Information is pre-handled to guarantee the data cleaning, expulsion of duplicates and normalization [36][37]. Figure 5 presents a gathering of references in the field of employability, featuring the researchers, distribution years, strength of reference, and the time spans in which these blasts happened [38].

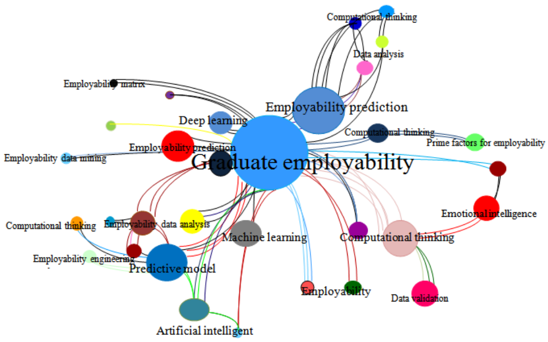

Fig. 5 Publication strength of authors in the "Employability"

Table 3 Network from keyword co-occurrence analysis using VOSviewer

Keyword	Occurrences	Published year (mean)	Links	Link strength
Employability prediction	42	2020	46	39
Predictive model	39	2018	32	30
Graduate employability	11	2019	18	15
Student performance	19	2015	26	21
Performance detection	15	2016	19	15
Student soft skill detection	86	2017	56	50
Computational thinking	7	2023	10	5
Emotional intelligence	6	2022	8	9
Factors affecting employability	4	2021	5	1
Data analysis for employability	3	2020	4	3
Employability	121	2018	6	5
Employability prediction using AI	15	2021	15	17
Machine learning based predictive	26	2020	16	8
Deep learning based predictive	31	2021	9	5
Employability matrix	7	2023	2	1
Feature optimization	5	2014	1	1
Data validation in employability	6	2015	3	2

3.4 Journal co-citation analysis

Journal co-citation analysis [39][40] is a bibliometric method that focuses on identifying connections between academic journals based on the co-citation of articles. For co-citation analysis, CiteSpace was loaded with the data, and boundaries were set. Table 4 describes the most refereed journal from the past prediction. Studies in educational evaluation, with its 21 related publications, have made significant contributions to the field.

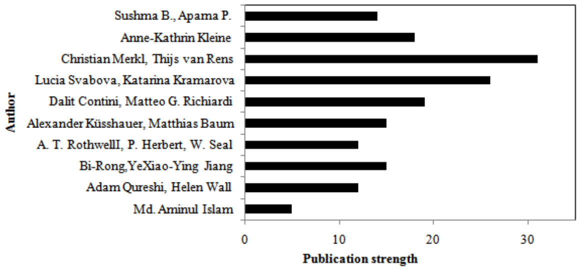

Fig. 6 Network of document co-citations analysis

Table 4 Top sources of journal articles of Employability

Author	Year	Strength	Begin	End
Md. Aminul Islam	2022	5	2015	2022
Adam Qureshi, Helen Wall	2021	12	2016	2021
Bi-Rong,YeXiao-Ying Jiang	2022	15	2011	2022
A. T. Rothwelll, P. Herbert, W. Seal	2018	12	2008	2019
Alexander Küsshauer, Matthias Baum	2023	15	2015	2023
Dalit Contini, Matteo G. Richiardi	2015	19	2001	2019
Lucia Svabova, Katarina Kramarova	2021	26	2016	2023
Christian Merkl, Thijs van Rens	2019	31	2011	2021
Anne-Kathrin Kleine	2021	18	2015	2023
Sushma B., Aparna P.	2022	14	2015	2022

3.5 Document co-citation analysis

Document co-citation analysis is bibliometric technique used in academic and scientific research to understand the relationships between scholarly documents based on how often they are cited together in other publications. Furthermore, it's worth noting that the modularity score exceeds 0.3, and the silhouette score surpasses 0.5 for this specific network, as depicted in Fig. 6.

3.6 Clustering analysis

Following the document co-citation analysis, the subsequent phase involves clustering the research documents in the field of graduate employability. Form SLR we leverage latent semantic indexing (LSI) and log-likelihood ratio (LLR) technique implemented using CiteSpace, to create a total of 7 distinct clusters. Table 5 provides information about these clusters. Notably, we observed that the "employability" cluster exhibits the largest size, identified through LSI, while the "predictive model for employability" cluster, identified through LLR, also boasts a substantial cluster size.

4. Existing work in graduate employability

In this section, we will delve into the clusters as outlined in Table 6 and provide an in-depth review of the highly cited documents within each cluster. Furthermore, we will perform an analysis of the research topics prevalent in these clusters, prioritizing them based on the relevance and the quantity of publications within the graduate employability research areas. This comprehensive SLR aims to shed light on the existing research on graduate employability and its various focal points.

4.1 Factors affecting employability

The SLR concerning employability and predictive models for employability prediction in the context of CS graduates is extensive and multifaceted. Clustering analysis has unveiled the interconnected nature of Cluster #1, #3, and #4 within the network. These clusters, through the application of LSI and LLR, reveal distinct thematic areas. Cluster #1, #3, and #4 collectively represent the underlying factors influencing the employability of CS graduates. The specific areas illuminated by these clusters are described as follows. In this SLR, we place a particular focus on two pivotal factors that play a significant role in influencing the employability of CS graduates: computational thinking (CT) and emotional intelligence (EI).

4.1.1 State-of-art studies on computational thinking

Computational thinking (CT) involves a structured and analytical approach to solving complex problems and designing mechanisms. Gonzalez et al. [58] have presented evidence of the reliability and criterion validity of a novel assessment tool designed to measure CT. Yagci et al. [59] have developed to assess the CT skills of high school students, and its validity and reliability were evaluated using data from 785 student participants. Gonzalez et al. [60] have addressed the issue by examining the connections between CT and fundamental cognitive variables, including primary mental abilities and problem-solving skills. Korucu et al. [61] have investigated the computational thinking skills of secondary school students while considering various variables. Doleck et al. [62] have explored the connection between CT and academic performance. Durak et al. [63] have investigated the extent to which various variables can account for students' CT skills. Tsai et al. [64] have utilized an impactful tool to assess all CT processes of students in various problem-solving contexts. Gong et al. [65] proposed an SEM analysis to investigate the main factors that influence students' learning and students' CT. Souto et al. [66] suggested assessing CT skills. Table 6 describes the tools used for factor analysis of CT from existing state-of-art works.

Table 6 Tools used for factor analysis of CT [58]-[66]

Cluster ID	Cluster size	Mean year	Most used items		Most citied
			LSI	LLR	
1	38	2016	Employability	Predictive model for employability	[49]
3	29	2014	Graduate employability	Computer science graduate	[50]
4	27	2019	Factors affecting employability	Prime factors	[51]
6	15	2021	Data analysis for employability	Data mining tools	[52]
7	12	2022	Employability matrix	Confusion matrix	[53]
9	7	2019	Machine learning based prediction	ML for employability prediction	[54]
12	6	2020	Deep learning based prediction	DL for employability prediction	[55]

4.1.2 State-of-art studies on emotional intelligence

Emotional intelligence (EI) pertains to the capacity to recognize, understand, manage, and effectively use emotions in various aspects of life, including in professional settings. Hendon et al. [67] have proposed an examination of soft skills utilized by IT experts with the connection between EI and correspondence versatility. Afeez et al. [68] have proposed the impact of EI capacity level. Chand et al. [69] have proposed to comprehend the job of employability and EI toward manager fulfillment in enrolling new data innovation designing alumni from foundations of higher learning. Pappas et al. [70] proposed a subjective relative study of fuzzy synthesis in an information test of 344 undergraduate students. Davis et al. [71] proposed the validation of a self-report measure of EI based on phenomenology and conceptualization. Meyer et al. [72] suggested that sensory experts converge on correct answers on tests and are more reliable than individuals from a general sample. Pathak et al. [73] have analyzed the IE concepts and aspects of the exams are the ultimate function of legal proof and prospective recruitment of new and active IT professionals. Fukuda et al. [74] contrasted Wong's 16-item Korean Interpretation and Discipline of Deep Understanding (WLEIS) with a sample of 161 Korean college students. Table 7 describes the tools used for factor analysis of EI form existing state-of-art works.

Table 7 Tools used for factor analysis of EI [67]-[74]

Ref.	Techniques	Tools used	Findings
[58]	Cattel-Horn-Carroll CHC)	R	Spatial ability, reasoning ability, problem solving ability
[59]	KMO and Bartlett tests	SPSS	Internal consistency level
[60]	BFQ-C	SPSS	CTs score
[61]	ANOVA	SPSS	Thinking skill ratio
[62]	Structural model-partial least squares	WarpPLS	Composite reliability, Average variance extracted
[63]	Structural equation model	SPSS	RMSEA, NFI
[64]	EFA, PCA with Oblimin rotation	MATLAB	MSE, RMSE, R2
[65]	EFA, CFA	SPSS	Absolute and incremental fit
[66]	CFA, PCA	R	RMSE, MAE

4.2 State-of-art studies on validate model for prime factors

In employability prediction, the confirmation of the identified factors holds utmost importance, primarily because of its profound influence on prediction accuracy. Our clustering analysis has revealed that Cluster #6 is indicative of the validation model for prime factors. Gregorio et al. [75] have analyzed how advanced change has disturbed the showcasing vocation way by breaking down the most popular promoting abilities and recognizing open doors for future advertising experts. Serim et al. [76] have investigated the connections between representatives' view of ability models and employability results as well as the relationship with the authoritative citizenship conduct. Mehreen et al. [77] have proposed the Fuzzy based validation model for analyzing the key objective and the functional length of optimal size. Priyadarshini et al. [78] proposed the hereditary calculation-based approval model to perceive thoroughness and employability. Nghia et al. [79] have proposed a vital part of numerous advanced education projects and temporary positions. Caputo et al. [80] have proposed the dynamic career scale (DCS), which estimates four unique methods of working in confronting professional disappointments as per Klein's item relations hypothesis. Arora et al. [81] have proposed that fundamental data has accumulated through India from the students. Unguren et al. [82] have explored to extracurricular understudy club enrollment status of the travel industry understudies influence vocation expectations and post-graduation employability. Bozionelos et al. [83] have proposed a quasi-experimental arrangement with assessment and attempted a model whose variables tended to key parts of the practical calling process as trapped in outstanding thinking. Zhong et al. [84] have proposed a control structure-based validation model for employability of postgraduate students. They utilized the different prime factors such as student skill sets and technical sets from the academic engagement. Audenaert et al. [85] have investigated how spreading out clear suspicions, developmental invitation, and various socially leveled targets can develop the employability capacities of feeble workers.

4.3 Employability Prediction Using Predictive Models

Employability prediction is the process of evaluating a person's ability to successfully perform a certain job or profession. Casuat et al. [86] have analyzed the student's employability prediction using different ML techniques. Bhagavan et al. [87] have proposed educational data mining (EDM) with the help of efficient data analytics tools. Moumen et al. [88] have proposed the ML technique for the student employability prediction model by using linear regression. Saini et al. [89] analyzed the employability opportunities after completion of the course by using different ML techniques. Aderka et al. [90] have analyzed the occurrence of sudden gain and their job opportunities towards that. Li et al. [91] have proposed a modified version of support vector machine (SVM) for employment prediction. Kumar et al. [92] have analyzed the MBA student placement performance using the Random forest model with the help of different factors such as skill impact, subject knowledge, and demographic characteristics. El-Sharkawy et al. [93] have proposed the hybrid technique called GNB and random forest for graduates' employability prediction. Saidani et al. [94] have proposed gradient boosting classifier for student employability prediction using the context-aware information of students. Fallucchi et al. [95] have proposed a prediction model for employee attrition using an SVM. The summary of review of the ML technique for employability detection is described in Table 8.

Table 8 Review summary of ML based predictive models for employability prediction

Ref.	Techniques	Tools used	Findings
[67]	SSEIT and CAS	R	Accuracy, RMSE and MAE
[68]	Cohen's d and single and multiple regression	SPSS	SSREIS, AMS and ASS
[69]	CFA, PCA	R	RMSE and MAE
[70]	fsQCA	MATLAB	Accuracy, precision
[71]	SEM,CFA	SPSS	Absolute and incremental fit
[72]	Multiple regression	R	Goodness-of-fit index
[73]	LAL and NHS	SPSS	RMSE and MAE
[74]	CFA, PCA	R	NNFI, CFI, RMSEA
[67]	SSEIT and CAS	R	Accuracy, RMSE and MAE

Table 9 Review summary of DL based predictive models for employability prediction

Ref.	Predictive model	Data collection	Performance measure (%)		
			Accuracy	Sensitivity	Specificity
[86]	Support vector machine	OJT course of School	91.220	89.562	85.978
[87]	HLVQ	Hindu college, Punjab	92.600	87.563	86.235
[88]	Linear regression	CSE-MUJ college	72.560	91.235	85.123
[89]	Decision tree	IT graduates from Egypt	89.000	88.025	79.568
[90]	Random forest	HRM dataset-US data	75.890	75.260	77.125
[91]	Support vector machine	CCIS-PNU 2019-2021	92.350	74.265	69.856
[92]	Random forest	IIT-Chennai	88.000	81.459	80.235
[93]	GNB and random forest	CSE-MUJ college	94.560	86.380	77.358
[94]	XGBoost, CatBoost, LGBM	MDU-CSR college	92.568	84.363	74.468
[95]	Support vector machine	OJT course of School	54.000	82.222	78.365

Roczniewska et al. [96] have investigated the availability of resources for job providers by using JD-R model which utilizes clustering information for prediction. Nie et al. [97] have proposed the adaptive cluster based XGBOOST model for students' career choice prediction by using information such as student programming skill, technical knowledge, and extra activities. Naz et al. [98] have proposed the predictive model for employee churn count prediction using the recurrent network with multiple layers. Tao et al. [99] have proposed the DL based predictive model for the student learning prediction using the clustering process. Ots et al. [100] have analyzed the employability factors on paid employment service by using the linear regression. The summary of review of techniques for employability prediction is described in Table 9.

5. Discussion

In this section, we examine the analysis and interpretation of SLR results. Here, we describe the identified employability factors in the context of employability prediction and discuss their implications. We analyze the relationship between these factors and how they affect the labor market and the employment prospects of individuals. In describing our findings, we aim to better understand the dynamics of employability prediction.

5.1 Analysis and interpretation of findings

SLR is a valuable tool for assessing performance and trends in a particular field of study through rigorous analysis. It can reveal key factors that contribute to the development of research in a particular field and provide important insights to help researchers search for more fruitful areas of study. In our SLR, we examine a dataset consisting of 578 articles from 71 different journals that focus on predicting graduate employment. After limiting our search to 1980 to 2023, we pulled this data from three primary sources: Web of Science, Scopes, and Lens. Our results show that most records were related to approximately 50.122%. In engineering, the remaining 12.569% are related to social sciences. In addition, in 2010 we noticed the highest publication activity 89 articles. Our comprehensive SLR sought to address specific research questions and thus provided valuable insights into the field.

1. Regarding **RQ1**, our SLR shows that research in employability predictive models has significantly explored the application of AI methods. Several studies show that the combination of AI techniques such as ML, DL, and NLP improves the accuracy and efficiency of employability prediction [86]-[100].

2. In response to **RQ2**, recent developments in employability prediction have shown significant developments over the years. The use of AI techniques has gained significant momentum, making forecasting models more accurate and sophisticated.

3. Regarding **RQ3**, the SLR analysis reveals several themes that explain the expected employment patterns of graduates, such as educational factors, skills and abilities, work experience, personal characteristics, economic and labor market factors, and demographic and social factors.

4. Response to **RQ4**, generally employability prediction covers different academic fields, reflecting the complexity and interdisciplinary nature of the field. Data science includes skills related to data collection, cleaning, analysis, and interpretation.

5. Response to **RQ5**, the identification of suitable factors for employability prediction remains a challenge, as does the development of effective validation tools for the selected prime factors. Additionally, the creation of a suitable predictive model for employability prediction presents its own set of challenges. In our future research, we will focus on addressing these issues.

5.2 Limitations of the Study

Most previous studies have focused on the employability of engineering and management students. Although there are several employability opportunities for CSE graduates, they often do not cover all the factors that affect the predictability of employability. These studies use different algorithms to predict occupancy, and the performance of these models, especially in terms of accuracy, varies by algorithm and data set. Additionally, differences in students' skill sets may account for differences in research findings across socio-demographic variables. This study focuses on the discipline of computer science engineering, which is at the heart of the academic field. It considers important factors of all stakeholders and aims to develop a predictive model that can improve the employability of computer engineering graduates.

6. Conclusions and future work

6.1 Summary of key findings

Enrollment in computer science engineering programs across the country has increased as a result of the proliferation of engineering and technology institutions, reflecting a broader trend. However, many of these young graduates lack essential job skills. Previous survey data shows that engineer unemployment in the Indian IT sector is: 18.43% in software services and 3.21% in software product development and business process outsourcing. The main issue is the selection of different types of universities, but the main goal is to secure employment that would continuously increase the country's GDP [101-102]. This is an important motivation for identifying recruitment factors. Despite the current employment challenges faced by recent cs graduates in India, there is little research in this area, particularly in the Indian context. Some studies examine the relationship between emotional intelligence and employability, others link technical skills to employability, and there are few studies examining emotional intelligence, technical skills, and employability. This study is a unique attempt to determine the relationship between emotional intelligence, computational thinking skills, and employability of computer science graduates.

6.2 Contributions to the field

The current SLR has uncovered many important areas, including data mining, employment, computational thinking, sentiment measurement, and employment forecasting. In the past, research has mainly focused on examining the isolated effects of emotional intelligence (EQ) or computational thinking (CT). However, these studies are often employer-based or international, and sometimes both. To address this research gap, there is a clear and urgent need for a study that comprehensively examines the three constructs of EQ, CT, and unemployment, particularly from the perspective of students in the specific context of India. Although several prediction models have been developed to predict the employability factors of engineering students, these models mainly use different supervised and unsupervised ML algorithms. Supervised learning such as decision trees and random forests and unsupervised learning such as k-nearest neighbors and neural networks are widely used. However, despite existing work, no predictive model has yet been developed that successfully integrates the combined effects of EQ and CT. This research gap highlights the need for predictive models that effectively integrate EQ and CT. The existing literature does not address whether EQ and CT are related or influence each other. This is a promising direction for future research that may provide valuable insights into the dynamic interactions of these constructs.

6.3 Future research directions

The SLR conducted in this study revealed several gaps and areas for further research. This research gap ranges from identifying factors influencing employment to developing composite employment indicators for employment forecasting. Based on the findings of SLR, the following areas are important for further research.

- To improve employability prediction models, future research should go deeper to identify the factors that have a significant impact on employment. An in-depth study of these factors will lead to more accurate and comprehensive forecasting models.
- It is important to develop evaluation models for selected work components. Developing robust tools to measure the employability impact of these factors will increase the reliability and accuracy of employability prediction models.
- The field of employability prediction will benefit from the development of forecasting models that incorporate multiple factors, including EQ and CT. These models aim to provide a comprehensive view of employability and its determinants.
- To fully understand employability and its dynamics, important to create an employment matrix. Future research should focus on developing and improving this policy and decisionmaking matrix.

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